PREDICTING EMPLOYMENT OUTCOMES FOR YOUTH WITH DISABILITIES IN ECONOMIC EMPOWERMENT PROGRAMS: A MACHINE LEARNING APPROACH

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Abstract

Youth with disabilities face significant barriers to employment, including discrimination, limited access to education, and inaccessible workplaces which contribute to high unemployment rates and social exclusion. To improve the effectiveness of economic empowerment programs for this demographic, this study developed a machine learning model to predict employment outcomes for youth with disabilities. Drawing from data of 895 youth with disabilities from the Bunyoro subregion of Uganda who participated in economic empowerment programs, encompassing demographic data, disability types, intervention details, and employment status at follow-up, we trained and evaluated several machine learning models. Among these were ensemble methods such as Random Forest, XGBoost, Gradient Boosting, and Stacking Ensemble. The Stacking Ensemble achieved the best performance with an accuracy of 97.21%, a precision of 92.73%, a recall of 98.08%, and an F1-score of 95.22% in predicting improved employment status. The key factors driving employment success were soft skills training, the provision of start-up kits, and the duration of the interventions. This research addresses the critical need to improve the effectiveness of economic empowerment initiatives developed to support youth with disabilities. The findings can inform other programs with similar contexts, contributing to broader development efforts and potentially inspiring the adoption of predictive modeling in other social programs targeting marginalized groups.

Keywords: *Economic Empowerment, Youth with Disabilities, Machine Learning, Predictive Modeling, Data-Driven Interventions, Predictive Analytics*

DECLARATION

I, Leonard Akoch (M23M19/253), declare that this dissertation is my original work and has not been submitted for any other degree or qualification at any university or institution.

APPROVAL

This dissertation has been submitted with my approval as the supervisor and my signature here appended against my names below.

Mr John Bosco Wabwire

Signature

Acknowledgements

I extend my sincere appreciation to my supervisor, Mr. John Bosco Wabwire, for his guidance and support on this dissertation. His input was crucial in shaping my research and understanding.

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List of Acronyms

AUC-ROC	Area Under the Curve - Receiver Operating Characteristic
DT	Decision Tree
FN	False Negative
FP	False Positive
IDD	Intellectual and Developmental Disabilities
KNN	K-Nearest Neighbors
LR	Logistic Regression
MFIs	Micro Finance Institutions
NCI-IPS	National Core Indicators In-Person Survey
PII	Personally Identifiable Information
RF	Random Forest
SCA	Saving and Credit Association
SOC	Standard Occupational Classification
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
TPR	True Positive Rate
UNESCO	United Nations Educational, Scientific and Cultural Organization

1. INTRODUCTION

1.1. Background Information

Despite the growing awareness in society and legislative efforts to promote inclusivity, youth with disabilities still face many challenges in accessing quality employment opportunities. They are persistently underemployed and experience more adverse effects of unemployment more than the rest (Tran et al., 2021). Widespread discrimination and prejudice worsen the situation, as it is evident that disabled job applicants are more likely to receive a negative response, fewer opportunities to attend interviews, and lower hiring rates when compared to those without disabilities (Ameri et al., 2015). This discrimination is a result of the implicit prejudices held by employers, deep-seated stereotypes about the capabilities of individuals with disabilities, and the ingrained barriers in the system of recruitment and hiring practices.

Apart from attitudinal barriers, physical and digital accessibility barriers pose considerable challenges to employment opportunities. Inaccessible workplaces, lack of accommodations, and inaccessible online job application portals impede the capacity of young people living with disabilities to compete equally (Gould et al., 2018).

Limited access to high-quality education and vocational skills training is a significant obstacle. UNESCO (2014) highlights that people living with disabilities encounter specific challenges concerning their right to education, thus promoting limited opportunities in traditional lines of study. Educational disadvantage prevents them from getting the skills and qualifications to secure employment, hence their further marginalization in the job market. Practical obstacles, including limited transport, heavily limit work opportunities. Inadequately established public transport and inaccessible transport facilities hinder the accessibility and mobility of work opportunities by youth with disabilities (Mwaka et al., 2024; Sabella & Bezyak, 2019). These transport barriers not only limit geographical access to the workplace but also limit access to employers and the general social networks in the community.

Additionally, the economic costs associated with disability like healthcare expenses, assistive devices, and support services pose additional challenges (Shahat & Greco, 2021). Such economic constraints often discourage youth with disabilities from participating in education or training programs that would enhance their prospects for employment, thus creating a cycle of disadvantage.

Given these complexities, this study undertook an analysis of economic empowerment programs designed to help youth with disabilities to become financially independent. By developing a predictive machine learning model, the study assessed the effectiveness of these programs and identified key drivers of success.

1.2. Problem Statement

Youth with disabilities face significant challenges in securing employment, leading to elevated rates of unemployment, poverty, and social exclusion, especially in resource-constrained developing nations. For example, in Uganda, 2017 data revealed that 17% of youth with disabilities were neither employed nor engaged in education or training, compared to 15% of their peers without disabilities (International Labour Organization, 2022). The underpinning of these disparities are societal biases and stereotypes that frequently result in discriminatory hiring practices and unwelcoming work environments (Lindsay et al., 2021).

While data-driven approaches and predictive modeling show the potential to improve employment interventions (Mezhoudi et al., 2021), their application in economic empowerment initiatives aimed at youth with disabilities in Uganda remains limited.

This study addressed this gap by developing a machine learning model to predict employment outcomes for youth with disabilities participating in economic empowerment programs and identifying key factors driving employment outcomes for this demographic. Through this dual approach, the research aspired to improve the efficiency of youth economic empowerment programs and foster more inclusive societies for marginalized persons in Uganda.

1.3. Justification

This study addresses the urgent need to improve the effectiveness of economic empowerment initiatives aimed at improving employment outcomes for youth with disabilities. Using advanced machine learning techniques to examine data from 895 youth with disabilities in Bunyoro subregion of Uganda who were participants in economic empowerment programs, this study methodically finds important drivers that predict successful employment outcomes, including financial resources, individualized mentoring and access to vocational training. These results give program administrators and legislators practical evidence-based advice on how to best tailor interventions to the particular requirements of this population. The findings can inform other programs with similar contexts, contributing to broader development efforts and potentially inspiring the adoption of predictive modeling in other social programs targeting marginalized groups.

1.4. Objectives

1.4.1. Main Objective

To develop and evaluate a predictive machine learning model to enhance employment outcomes for youth with Disabilities.

1.4.2. Specific Objectives

1. Identify and evaluate factors contributing to employment success
2. To develop a predictive machine learning model incorporating key variables
3. Assess the model's performance and impact on interventions

1.5. Research Questions

1. What factors drive successful employment for youth with disabilities in existing economic empowerment programs?.
2. How can a machine learning model predict employment outcomes?.

3. How effective is the model in predicting employment outcomes?.

1.6. Study Scope

The study focused on 895 youth with disabilities in Bunyoro subregion of Uganda who were participants in economic empowerment programs implemented by Uganda’s Ministry of Gender, Labour and Social Development from 2021-2023.

2. LITERATURE REVIEW

2.1. Introduction

The literature review investigated previous research on using machine learning to predict employment outcomes for youth with disabilities with a focus on identifying gaps in low -income countries like Uganda. By reviewing these studies, we aimed to uncover strategies that can improve employability for this vulnerable population.

2.2. Disabilities and Related Challenges

Youth with disabilities face a multitude of challenges that affect their ability to secure employment, especially in low-income countries where there is scarcity of resources. Access to quality education, which is a foundation to economic empowerment, remains difficult to access for this demographic. Babik and Gardner (2021) assert that, there is low acceptance among children with disabilities by their peers in schools, restricting their full participation. This trend is evident in a report *Situation Analysis of Persons with Disabilities in Uganda* by Kett et al. (2020), which reported that young people with disabilities have a harder time finding decent employment because they are less educated than their peers without disabilities, leading to higher unemployment rates.

Beyond education, socio-cultural factors play a substantial role. As stated by Centers for Disease Control and Prevention (2024), cultural and social barriers are related to the circumstances around the births, development, lifestyle, education, employment, and aging of individuals, leading to reduced functionality in individuals with disabilities. Cultural influences shape the perceptions and treatment of individuals with disabilities in society, resulting in limited employment opportunities, lower rates of educational attainment, reduced income, and increased instances of violence (Okoth & Wamalwa, 2022). Similarly, Requero et al. (2020) noted that institutional and societal barriers still exist for people with disabilities, which can affect both their performance at work and their ability to get employment. According to the Ministry of Gender, Labour and Social Development (2023), discrimination based on disability is prohibited in Uganda, although prejudice and misunderstanding still exist within communities.

Economic challenges such as inaccessible transportation means and lack of financial resources further complicate the situation. For example, Otieno (2013) discusses how people with disabilities in rural Kenya face greater challenges in gaining access to employment, education, healthcare, social interaction, and recreational activities due to transportation barriers. A similar situation was observed in India, where Sarkar (2023) noted that discrimination and inaccessibility forced women with disabilities to informal work that is available to them.

These combinations of barriers highlight the critical need for targeted interventions in places like Uganda where research on disability and employment remains limited.

2.3. Drivers of successful employment in employment programs for youth with disabilities

Several studies highlight factors enabling successful employment among youth participating in economic empowerment programs. Alfonsi et al. (2018) suggested that having vocational skills encouraged disadvantaged youth in Uganda to explore various job opportunities, and as a result, apprenticeships and vocational training enhanced access to employment for these underprivileged young people. Individuals with disabilities frequently need ongoing services and support that involve help with daily tasks like transportation, assistance in attending educational institutions, and the coordination of regular care (Okoth & Wamalwa, 2022). Fox and Gandhi (2021) suggested that the lack of access to resources, land, and equipment is a significant factor in youth unemployment in Sub-Saharan Africa. These essential tools encompass the raw materials needed to produce items such as handmade furniture, food products, or hairdressing equipment. This is similar to the suggestion by Shiferaw (2020) that providing tools and equipment can enhance the job prospects of youth in Ethiopia. Additionally, Rajeev et al. (2017)

conducted a study on promoting entrepreneurial growth among young people to generate job opportunities through industrial advancement at the Zanzibar Technology and Business Incubator (ZTBI), which showed that providing entrepreneurship education and start-up assistance can economically empower youth.

The studies focused mainly on general youth, neglecting the much-needed attention to youth with disabilities in Uganda. Moreover, previous studies have not taken advantage of machine learning to identify or optimize drivers to produce the best employment outcomes for this demographic.

2.4. Efficacy of Economic Empowerment Programs

Economic empowerment programs are initiatives designed to foster financial independence and sustainable employment among marginalized groups such as youth with disabilities. These programs typically include vocational training, access to microfinance, entrepreneurship development, and other supportive measures that address specific barriers faced by these individuals in the labor market (Levin et al., 2023).

Several studies indicate that training and financial support can improve youth employment outcomes. For example, youth training opportunies in Mongolia effectively enhanced earnings and job opportunities in the short and medium term (Batchuluun et al., 2017), while participants in Chile's "Formacion para el Trabajo (FOTRAB)" program experienced an increase in their income in the short term (Doerr & Novella, 2020). However, Shiferaw (2020) discovered that although they received training, the beneficiaries of the pastoral project in the Afar, Eastern, and Southern clusters of Ethiopia remained unemployed due to insufficient financial support and weak connections with industry employers. Alam and Azad (2021) also revealed that Micro Finance Institutions (MFIs) in Ethiopia enhanced the income and employment levels of their female clients.

Asadullah et al. (2021) highlighted that access to microfinance institution (MFI) services enhanced the employability of women clients in Bangladesh. The research revealed that the financial services offered by MFIs empowered women, leading to greater independence and improved financial and health satisfaction, resulting in overall happiness. Datta and Sahu (2021) found that in West Bengal, India, loans from MFIs enabled borrowers to elevate their employment levels and, consequently, their livelihoods. Chandrashekhar and Sultani (2021) disclosed that MFIs in Afghanistan, by providing loans to entrepreneurs, bolstered their savings, income, and created more employment opportunities.

The successes in the studies may not be directly applicable in Uganda's structural and socio-cultural context. Importantly, they do not directly assess the role of economic empowerment programs specifically targeting the employability of youth with disability in Uganda which limits program design.

2.5. Machine Learning Approaches for Employability Prediction

2.5.1. Logistic Regression

Logistic Regression (LR) is a supervised machine learning technique used for binary classification problems by predicting the likelihood of an event, outcome, or observation occurring. The model produces a binary or dichotomous result, limited to two possible outcomes, such as yes/no, 0/1, or true/false (Hastie et al., 2009).

Sobnath et al. (2020) utilised Logistic Regression and other algorithms to examine employment outcomes for students with disabilities, analyzing over 270,000 records from the Higher Education (DLHE) dataset covering the years 2012 to 2017. The study answered two research questions: "(1) Can machine learning algorithms analyze extensive datasets of former disabled students to offer insights into their employability? and (2) Is it possible to develop an effective predictive platform based on the identified characteristics to forecast their type of employment?". A significant finding revealed that having a "First Class" honors degree is not a reliable indicator of securing full-time employment. The researchers tested multiple algorithms to predict three outcomes six months post-graduation: Activity, Industry, and Standard Occupational Classification

(SOC). Logistic Regression, Linear Discriminant Analysis, Decision Tree, and Gaussian NB performed poorly for Activity and Industry predictions, but Decision Tree Classifier and LR achieved 96% accuracy for SOC. However, this approach's reliance on large datasets may limit its feasibility in resource-constrained settings like Uganda.

2.5.2. Decision Trees

Decision Trees (DTs) are a non-parametric supervised learning method used for classification and regression (Scikit-learn, n.d.).

Griffiths et al. (2023) employed decision trees to forecast career trajectories for individuals with autism, drawing from 236 survey responses. Their classification tree model reached an accuracy of 93% and a specificity of 85% in identifying whether the participants had earned money from work.

While they are effective for handling non-linear data, decision trees can be prone to overfitting, especially when dealing with smaller datasets, a challenge that can be mitigated by using ensemble methods.

2.5.3. Random Forest

Poonia et al. (2021) describe Random Forest (RF) classifier as an ensemble technique that simultaneously trains multiple decision trees using bootstrapping methods and then combines their results, a process known as bagging. Bagging, or bootstrap aggregating involves training individual decision trees on randomized subsets of the examples within the training set. In essence, each decision tree within the random forest is trained on a distinct subset of examples.

Researchers (Broda et al., 2021) investigated the application of machine learning as an inductive analytical tool to guide practice and policy for people with intellectual and developmental disabilities (IDD). Leveraging data from the National Core Indicators In-Person Survey (NCI-IPS), a validated yearly survey encompassing over 20,000 representatives with intellectual and developmental disabilities (IDD), the researchers used classification tree and Random Forest (RF) models to predict employment status and engagement in day activities. Their RF classifier, recognized as the most precise model, reached an accuracy of 89% on the test sample and 80% on the holdout sample. By analyzing data from the 2017–2018 NCI-IPS, the research highlighted the potential of RF in evidence-based policymaking, providing a strong method for predicting employment outcomes and improving decision-making for individuals with IDD.

2.5.4. Support Vector Machines

Sun and He (2023) underscore the effectiveness of the Support Vector Machine (SVM) model in forecasting student employability, highlighting the vital importance of feature extraction and machine learning techniques. Their research explored the impact of student orientation on the benefits received. Utilizing a t-test (α=0.05), they analyzed how orientation (independent variable) influenced compensation (dependent variable) and assessed significant differences between male and female students. Findings from various machine learning models revealed that SVM consistently surpassed other models in all evaluation metrics. In particular, SVM attained 90% precision, 92% recall, 85% accuracy, and an 88% F1 score (with $C = 0.01$ using a linear kernel). Although other models performed admirably as well (for instance, Logistic Regression recorded 88% precision, while Random Forest and XGBoost both achieved 83% precision), the SVM model showcased the highest accuracy rate of 93% in predicting employment status.

2.5.5. Results from selected Machine Learning models for employability prediction

This section summarized the results of machine learning algorithms used in the employability prediction study, focusing on key metrics like accuracy, precision, and recall. The performance of each algorithm is evaluated based on its ability to predict employability outcomes, highlighting their strengths, limitations, and real-world applicability.

Table 2.1: Machine Learning Studies on Employment Prediction

Study	Dataset	ML Model	Precision	Recall	F1-Score	Accuracy
1. "Feature Selection for UK Disabled Students" Engagement Post Higher Education: A Machine Learning Approach for a Predictive Employment Model" (Sobnath et al., 2020)	270,934 student records with a known disability	Logistic Regression	0.96	0.96	0.96	0.96
2. "Enhancing employment outcomes for autistic youth: Using machine learning to identify strategies for success" (Griffiths et al., 2023)	236 caregivers of autistic individuals	Decision Tree Classifier		0.93		
3. "Using Machine Learning to Predict Patterns of Employment and Day Program Participation" (Broda et al., 2021)	20,000 nationally representative people with intellectual and development disabilities	Random Forest				0.89
4. "Developing intelligent hybrid DNN model for predicting students' employability – A Machine Learning approach" (Sun & He, 2023)	-	Support Vector Machine	0.90		0.88	0.93

2.6. Limitations of current research

Prior studies exhibit notable limitations, for instance the studies by Sobnath et al. (2020) and Broda et al. (2021) were conducted in developed countries, neglecting the unique challenges of low-income settings like Uganda. Additionally, reliance on simpler models like Logistic Regression in some studies fails to address the complexity of employment outcomes for youth with disabilities. Advanced ensemble methods could potentially address this by managing non-linear relationships and reducing overfitting risks. This research filled the gaps by focusing on youth with disabilities in Uganda a low-income and employing advanced ensemble methods to handle complex, non-linear data.

3. METHODOLOGY

3.1. Introduction

This section outlines the methodological approach employed for predicting the employment outcomes of youth with disabilities in economic empowerment programs. It covers the study design, data preprocessing, model selection, and evaluation techniques, with implementation details provided in Chapter 4.

3.2. Study Design

This study utilized quantitative predictive modelling strategy based on supervised machine learning classification. It analyzed structured economic empowerment program dataset from Bunyoro Subregion of Uganda. The variables included were age, gender, education level, disability type, employment status at entry, interventions received, duration of interventions, accomodation support and employment status at follow-up. Since the dataset already contained known follow-up outcomes, supervised machine learning models could learn patterns from historical program data and then be test on unseen data. The model development process included data preprocessing, feature engineering, feature selection, train-test splitting, hyperparameter tuning, cross-validation and final evaluation using classification metrics.

3.3. Ethical Considerations

This research adhered to the principles of confidentiality, anonymity, and data protection given its focus is on a vulnerable population. All participants' data from source were anonymized prior to analysis, ensuring no Personally Identifiable Information (PII) was included. Approval from the relevant research ethics committee was sought to ensure the anonymization process meets ethical standards.

3.4. Data Source

This study utilized secondary program data from economic empowerment programs conducted by Ministry of Gender, Labor and Social Development over a span of three years starting from 2021. Anonymized data was shared of 895 participants in XLS format having observations for youth with disabilities who were beneficiaries of economic empowerment programs in Uganda. The variables included age, gender, education level, disability type, and employment status before and after program participation as described in Table 2 below.

Table 3.1: Description of Variables in the Dataset

Variable	**Description**	**Data Type**
Unique ID number	Participant's Unique ID.	int64
Age	Age of Participant	int64
Gender	Gender	Object
Highest Education Level	Highest Level of Education	Object
Impairment Data	Disability Type	Object
Employment Status at Entry	Participant's employment status at joining the program	Object
Intervention 1	First intervention given to participant at joining the program. (Internship Opportunity, Soft Skills Training, ICT Training, Startup Kit, Mentorship, Other)	Object
Duration 1	Duration of first intervention	float64
Outcome 1	Outcome of the first intervention	Object
Intervention 2	Second Intervention given to participant	Object
Duration 2	Duration of second intervention	float64
Outcome 2	Outcome of the second intervention	Object
Relevant Accommodation	Whether participants required support in transport, assistive devices, Airtime, Internet etc with options of Yes/No	Object
Employment status of participant at follow-up	Employment status of participant at follow-up	Object
Improved Employment Status	Whether participant shows an improvement on employment status	Object
Improved Labour Force Participation	Comparison of participants employment status at enrolment and at follow up	Object

A quick look at the statistics, shows 895 observations with the age variable having a standard deviation of 5.62 meaning most of the participants are clustered close to the average age of 27. Outliers in age can also be seen given the context of the data being for youth. This called for preprocessing as the next steps.

Table 3.2: Descriptive Statistics of Numerical Variables

	Unique ID number	Age	Duration_1	Duration_2	Duration_3
count	895	878	875	211	52
mean	20 574.921	26.884	47.513	99.270	128.288
std	337.657	5.624	64.436	122.101	111.667
min	20 002	17	25	25	25
0.25	20 273.5	23	27	25	25
0.5	20 580	26	32	25	167.5
0.75	20 865.5	29	35	183	183
max	21 167	62	351	351	351

Table 3.3: Distribution of Categorical Variables

Variable	**Count**	**Percentage**
Gender		
Male	487	54.40
Female	408	45.59
Highest Education Level		
Diploma / associate degree	319	38.07
First degree	203	24.22
Vocational training	162	19.33
Secondary	113	13.48
Other	15	1.79
Postgraduate	13	1.55
Primary	7	0.84
No education	5	0.60
Pre-primary	1	0.12
Employment status at entry		
Actively seeking employment	768	85.81
Unemployed and not seeking employment	32	3.58
Waged employment	26	2.91
Self-employed	26	2.91
Other	20	2.23
Actively seeking self-employment	20	2.23
Payment in kind	3	0.34
Improved Employment Status		
No	637	71.17
Yes	258	28.83

3.5. Social and Economic Determinants Considered in the Study

The study considered various social, economic and disability-related, and program level determinants that could affect employment outcomes among youth with disabilities in economic empowerment programs. Social and demographic determinants included age and gender, while human capital determinants included highest education level, soft skills training, and ICT Training. Disability related determinants included impairment/disability type and relevant accomodation.

Economic and program related determinants included employment status at program entry, startup kit provision, intervention type and duration of support received in the economic empowerment program.

3.6. Data Preprocessing

Data pre-processing was a critical step in ensuring the raw data was cleaned, transformed, and structured appropriately for analysis and modeling. Proper pre-processing was crucial to remove noise, handle missing values, and ensured that the data was in a format that could be effectively used by machine learning algorithms. Libraries such as pandas, SciPy, NumPy were used and data pre-processing steps involved.

3.7. Model Selection

Given the binary nature of the outcome variable, improved_employment_status', classification models were deemed appropriate for this study. The selection of supervised learning algorithms was informed by a comprehensive review of recent comparative analyses, ensuring that the chosen models were both theoretically sound and empirically validated for similar tasks.

A foundational study by Sheth, Tripathi, and Sharma (2023) conducted a detailed evaluation of various classification algorithms across multiple datasets, utilizing a 70-30 train-test split. Their analysis assessed model performance based on key metrics, including accuracy, recall, precision, and F1 score. The results indicated that the Naive Bayes classifier outperformed other algorithms, followed by Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Trees. This comparative analysis provided a robust starting point for model selection in the present research, influencing the inclusion of KNN and Decision Trees as Baseline models.

Additional studies further informed us of the choice of algorithms. Sobnath et al. (2020) emphasized the effectiveness of Logistic Regression in binary classification tasks akin to this study, highlighting its interpretability and performance on similar datasets. This informed its inclusion as in the list of baseline models. Griffiths et al. (2023)) demonstrated the strength of Random Forest in handling complex, high-dimensional data, making it a suitable candidate for this investigation. Broda et al. (2021) and Sun and He (2023) offered complementary insights into the adaptability and robustness of SVM and Decision Trees, respectively, across diverse data characteristics.

For the baseline models, we evaluated Logistic Regression, Decision Trees, and K-Nearest Neighbors, given their simplicity, interpretability, and established performance in binary classification tasks, as evidenced by the literature. Performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC were computed to assess their effectiveness on the dataset. Building on this, an ensemble approach was incorporated with more sophisticated models - Random Forest, XGBoost, and Gradient Boosting to maximize predictive accuracy and efficiency.

Random Forest was included because it is well-suited to structured tabular data and it does capture non linear relationships between participants' charateristics, intervention variables, and employment outcomes. It also reduces overfitting risks associated with a single decision tree by combining many trees. XGBoost was included because of it's powerful boosting algorithm that performs well on structured datasets and improves prediction by sequentially correcting errors made by previous trees. These models were integrated into a Stacking Classifier with Logistic Regression as the final estimator. The Stacking Ensemble leverages the strength of individual models as noted by Wong et al. (2020), who stressed that while simple classification algorithms produce a single, interpretable model, they often fail to achieve high accuracy. In contrast, a hybrid approach can enhance performance by correctly classifying instances that might be mispredicted by an individual model.

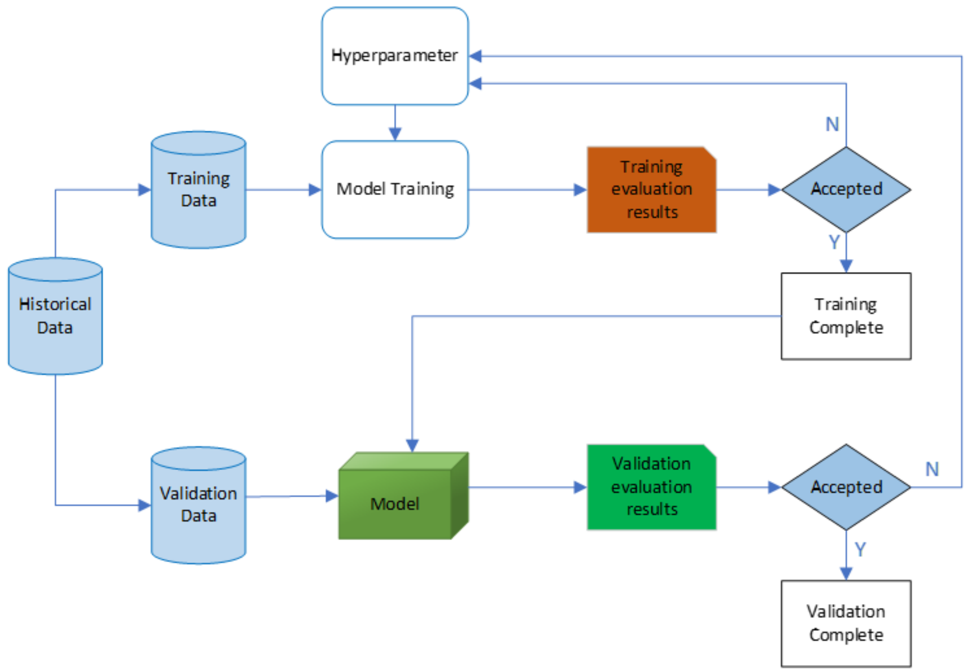

Figure 3.1: High Level Model Development Diagram

3.8. Model Evaluation

The proper use of techniques for model evaluation, selection, and algorithm choice is crucial in both academic research on machine learning and various industrial applications, as it guarantees that models are dependable and have good performance on data that has not been encountered before (Raschka, 2018). Cognizant that model evaluation and validation are crucial steps in machine learning process and thus our research, this study implemented a robust framework to assess the performance of the developed classification models. We used various metrics and techniques to validate the ensemble model, focusing on their performance in predicting the binary outcome ‘improved_employment_status’. These methods are discussed below.

3.8.1. Confusion Matrix

In this research, the Confusion Matrix served as a fundamental assessment instrument to evaluate the effectiveness of classification models in predicting the binary result of Improved Employment Status. This approach facilitated the recognition of four essential classification outcomes.

1. True Positives (TP): Being participants correctly predicted with status ”improved employment status”.
2. True Negatives (TN): Being participants correctly predicted with the predicted status ”employment status not improved”.
3. False Positives (FP): Are those participants where the model incorrectly predicted the ’Improved Employment Status” also known as (Type 1 Error).
4. False Negatives (FN) Are those participants where the model incorrectly predicted the ’No Improved Employment Status’ also known as (Type 2 Error).

3.8.2. Classification Accuracy

This metric represents the proportion of total predictions that were correct, It provides an overall measure of the model’s correctness across both positive and negative classes calculated as

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

3.8.3. Precision, Recall and F1-Score

1. Precision (Positive Predictive Value): Is the proportion of positive predictions (improved employment status) that were accurate calculates as

$$\text{Precision} = \frac{(TP}{(TP + FP)}$$

Precision is very important when cost of false positives is high.

2. Recall (sensitivity): This measures the proportion of actual positive cases correctly identified, computed as

$$\text{Recall} = \frac{(TP}{(TP + FN)}$$

Also known as the true positive rate (TPR), recall is critical in scenarios where missing positive cases (false negatives) is costly.

3. F1-score: As the harmonic mean of precision and recall, the F1-score provides a balanced measure of model performance, especially useful when the class distribution is imbalanced. It is defined as:

$$\text{F1 - Score} = \frac{2.Precision.Recall}{Precision + Recall)}$$

3.8.4. AUC-ROC

Due to its independence of the change in the proportion of responders, we used the AUC-ROC curve to evaluate our model. The Receiver Operating Characteristics (ROC) curve was utilized to visually represent the true positive rate (TPR) alongside the false positive rate (FPR) across various classification thresholds. The Area Under the Curve (AUC) served as an indicator of the overall effectiveness of our binary classification model.

4. MODEL IMPLEMENTATION

4.1. Introduction

This chapter describes the implementation of the machine learning models to predict employment outcomes for youth with disabilities participating in economic empowerment programs. Building on the methodology, we detail the development environment, data preprocessing, feature engineering, model building, training and evaluation setup.

4.2. Development Environment

We conducted our model development using Python 3.8 in Jupyter notebooks within Azure Data Studio using libraries such as Pandas for data manipulation, Scikit-Learn for machine learning models, preprocessing and evaluation metrics, and SciPy. The project was executed on a Windows 11 computer with AMD Ryzen 7 (1.70 GHz) processor and 16gb RAM.

4.3. Data Preprocessing

Data pre-processing is a critical step in ensuring raw data is cleaned, transformed, and structured appropriately for analysis and modeling. Proper pre-processing is crucial to remove noise, handle missing values, and ensure that the data was in a format that could be effectively used by machine learning algorithms. Libraries such as pandas, SciPy, NumPy were used in the steps below;

4.3.1. Handling Missing Values

Missing values were handled in numerical values (int64 and float64 data types) using the Iterative Imputer, a technique that estimates missing values based on relationship with other features in the dataset (Bertsimas et al., 2021). For categorical columns (data type object), missing values were filled with the most frequent value (mode) of each column, determined using pandas' mode() function. In rare cases where a column's mode could not be determined (e.g., if all values were missing), the string 'Missing' was used as the imputed value.

Variable	Missing
Unique ID number	0
Age	17
Gender	0
Highest education level	57
Employment status at entry	0
Impairment data	0
Outcome 1	16
Intervention2	683
Outcome 2	683
Intervention1	0
improved employment status	0
Duration 1	20
Duration 2	684
Relevant Accomodation	0

Table 4.1: Missing Values by Variable

4.3.2. Data Cleaning

Erroneous, duplicate, or inconsistent entries were identified and corrected to ensure the dataset's reliability. Outliers in the other variables were managed using statistical techniques such as transformation and capping based on their distributions. For the age variable, we applied domain knowledge specific to Uganda's youth age range, capping values to 15-30 to ensure contextual relevance.

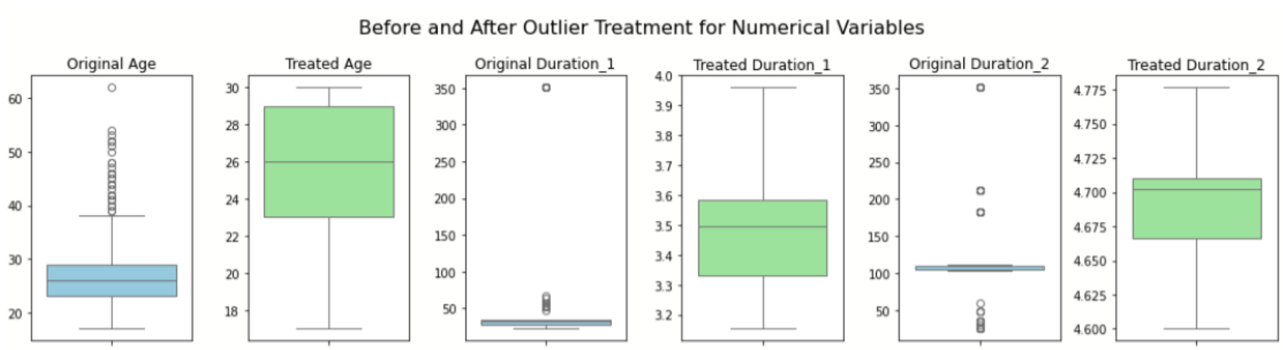

Figure 4.1: Outlier Handling

4.3.3. Feature Engineering

To prepare the dataset for analysis, a feature engineering pipeline was implemented using Python with the pandas and numpy libraries. This pipeline transformed the raw data into a more structured and interpretable format by creating new features that capture key patterns and relationships. Irrelevant or redundant features were removed e.g. participants' unique ID. These engineered features include:

(a) Total Duration which sums up the time spent across interventions (i.e. duration1, duration2), capturing cumulative exposure.

(b) Education Group that categorizes education levels (e.g., "Low," "Medium," "High", "other") for simpler analysis.

(c) Age Group where age is grouped into bins (e.g., "15-19","20-24," "25-30") to identify trends across age ranges.

(d) Pairwise Intervention Presence, which is a binary indicator (1 or 0) for whether specific pairs of interventions (e.g., "ICT Training" and "Soft Skills Training") were both present for a participant, generated using combinations of intervention types.

(e) Sequence-Specific Features, a binary indicator (1 or 0) for specific sequences of interventions, such as "ICT Training" followed by "Soft Skills Training" or "Mentorship" followed by "Soft Skills Training," based on the order in Intervention1 and Intervention2.

Irrelevant or redundant features were removed e.g. participants unique ID, and new meaningful features were created where necessary to enhance model performance.

4.3.4. Encoding and Normalization

Using Python's pandas, numpy and sklearn libraries, we implemented an encoding and normalizations pipeline to prepare the dataset for machine learning. The target variable was label-encoded with LabelEncoder (”Yes” to 1, ”No” to 0). For linear models, categorical features were one-hot encoded using OneHotEncoder (with the first category dropped to avoid multicollinearity). For tree-based models, label encoding was applied. Numeric features were standardized with StandardScaler (mean = 0, standard deviation = 1). Class weights were calculated based on target class frequencies to address imbalance, supporting model optimization.

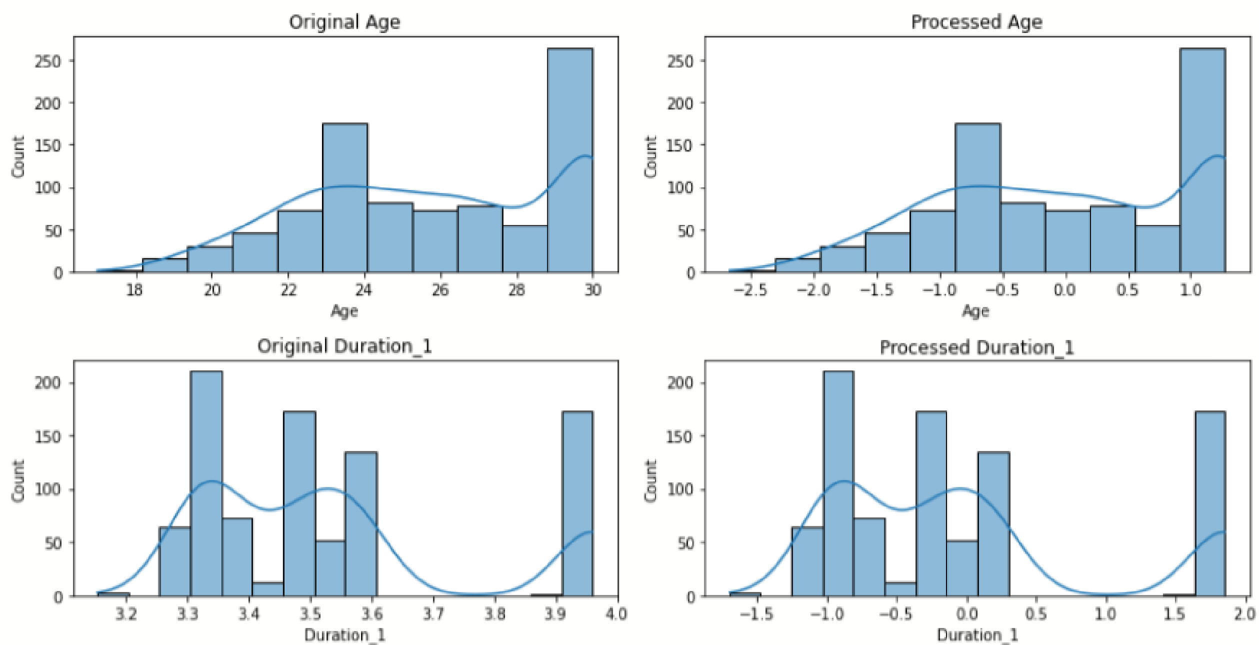

Figure 4.2: Feature Scaling and Normalization

4.3.5. Data Splitting

The dataset was split into 80 training and 20% test sets using scikit-learn’s train test split to evaluate the model’s performance effectively and prevent overfitting. A stratified split based on the target ’improved employment status’ ensured consistent class distribution, with a random state of 42 for reproducibility.

4.3.6. Feature Selection

The feature selection process was designed to identify and retain the most pertinent variables that could enhance the prediction of improved employment outcomes for youth with disabilities, while also improving model performance and minimizing dimensionality. It commenced with the application of domain expertise and correlation analysis to eliminate irrelevant or redundant features. Subsequently, A Random Forest classifier was trained on the dataset to evaluate the importance of each feature. Features with important scores exceeding the mean importance were selected. The selected features were then consistently applied to the training and testing datasets.

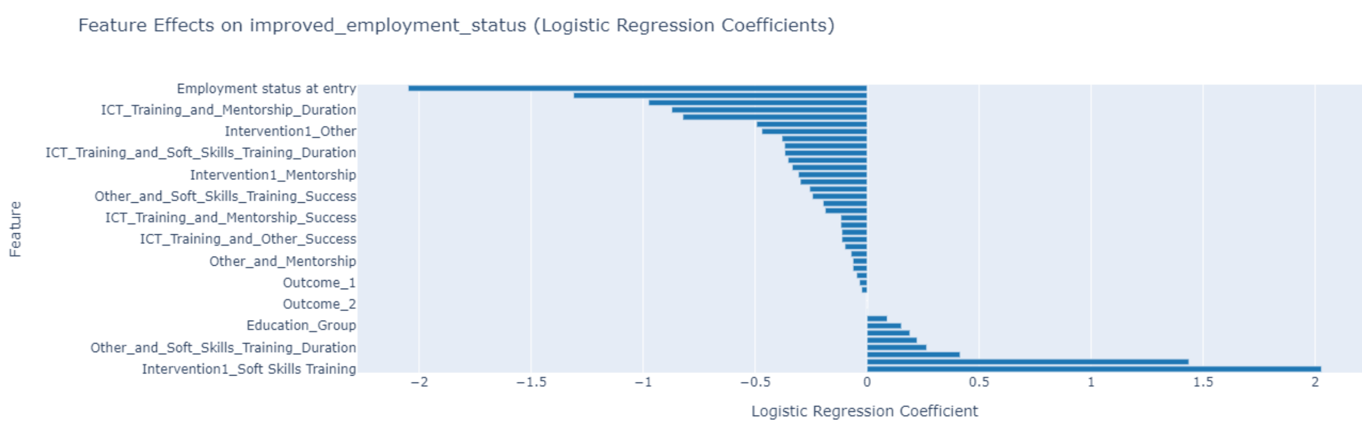

Figure 4.3: Feature Selection

Selected features included ('Intervention1 Internship Opportunity', 'Intervention1 Soft Skills Training', 'Intervention1 Startup Kit', 'ICT Training and Soft Skills Training', 'ICT Training and Other Duration', 'ICT Training and Soft Skills Training Duration', 'ICT Training and Mentorship Duration', 'Other and Soft Skills Training Duration', 'Soft Skills Training and Mentorship Duration', 'Employment status at entry')

4.4. Model Building

In our study, we employed two distinct machine learning pipelines to predict employment outcomes. The first pipeline focused on baseline models, while the second pipeline leveraged ensemble models for improved accuracy and robustness.

4.4.1. Baseline Model Pipeline

The baseline pipeline included simple yet effective models for binary classification described below

(a) Logistic Regression which is a linear model estimating probabilities via a logistic function, was configured with a max_iter=100,c=0.001, and random_state=42 for convergence and reproducibility.

(b) Decision Tree a tree based model with max_depth=2 to limit prevent overfitting using random_state=42 for consistency.

(c) K-Nearest Neighbors (KNN) an instance-based learner classifying based on the majority class of 100 nearest neigihbors balancing bias and variance These models were selected for their common use initial exploratory data analysis.

4.4.2. Ensemble Model Pipeline

To capture complex patterns, we employed an ensemble model with the following models;

(a) Random forest as ensemble decision tress with aclass-weigh='balance' to address class imbalance in the target variable "improved_employment_outcomes" but also to reduce overfitting via bugging and feature randomness.

(b) XGBoss a gradient boosting model with scale_pos_weight=3 to handle imbalance and eval_metric='logloss' for optimisation, known for efficiency in structured data

(c) Gradient Boosting a sequential boosting method with default settings

(d) Stacking Ensemble a meta-model combining predicitions rom Random Forest, XGBoost, and Gradient Boosting using Logistic Regression as the final estimator, inspired by the idea of leveraging diverse models to increase predictive power and better generalization.

4.5. Model Training

We trained the selected baseline models (Logistic Regression, Decision Trees, KKN) and Ensembles (Random Forest, XGBoost, Gradient Boosting) using pre-processed data which involved solid steps to ensure the models were optimized and generalizing well to new data. The data was split into training (80% test and testing (20%) sets to evaluate the model performance on unseen data.

4.6. Hyperparameter Tuning

Hyperparameter tuning was conducted to optimize the performance of ensemble model, specifically the ensembles Random Forest, XGBoost, and Gradient Boosting classifiers.

Hyperparameter	Random Forest	XGBoost	Gradient Boosting
n_estimators	$[50, 100, 200, 300]$	$[100, 200, 300, 500]$	$[100, 200, 300]$
max_depth	$[5, 10, 15]$	$[3, 5, 7, 9]$	$[3, 5, 7]$
min_samples_split	$[2, 5, 10, 20]$	N/A	N/A
min_samples_leaf	$[1, 2, 5, 10]$	N/A	N/A
max_features	'sqrt', 'log2'	N/A	N/A
learning_rate	N/A	$[0.01, 0.05, 0.1, 0.2]$	$[0.01, 0.05, 0.1, 0.2]$
subsample	N/A	$[0.6, 0.8, 1.0]$	$[0.8, 1.0]$
colsample_bytree	N/A	$[0.6, 0.8, 1.0]$	N/A
gamma	N/A	$[0, 0.1, 0.2]$	N/A
reg_alpha	N/A	$[0, 0.1, 1]$	N/A
reg_lambda	N/A	$[1, 10]$	N/A

Table 4.2: Hyperparameter Ranges for Different Ensemble Algorithms

4.7. Cross Validation

To enhance the robustness of hyperparameter selection and address the bias-variance trade-off, 10-fold cross-validation was implemented using the RandomizedSearchCV function from the sklearn.model_selection module. This technique partitions the training data into 10 equal subsets, ensuring class distribution is preserved in each fold as this classification task had imbalanced classes. For each combination of hyperparameters, the model was iteratively trained on 9 subsets and validated on the remaining subset. The F1-score was averaged across 10 folds to provide a reliable estimate of the models' generalizability. This process helped prevent both underfitting and overfitting as discussed in (Smith et al., 2024). This cross-validation approach was key in tuning the hyperparameters of base models – Random Forest, Gradient Boosting, and Gradient Boosting before integration into a stacking ensemble.

5. STUDY FINDINGS

5.1. Introduction

In this chapter, we present our findings on the study of predicting employment outcomes for youths with disabilities enrolled in economic empowerment programs in Uganda. Using machine learning algorithms, we analyzed data from 895 participants to uncover what really drives employment success. Central to our analysis was the development of a Stacking Ensemble model, which integrates multiple algorithms to predict employment outcomes.

5.2. Participant Demographics

The research gathered and analyzed demographic data of the 895 participants, providing insights into their age, gender, level of education, type of disability, and employment status. This information was crucial in identifying patterns in employment accessibility and the challenges faced by different groups of youths with disabilities.

5.2.1. Age Distribution

Table 5.1: Descriptive Statistics of a Age

Statistic	Value
count	895
mean	25.79
std	3.30
min	17
25%	23
50%	26
75%	29
max	30

As seen in table 5.1 above, the participants' ages ranged from 17 to 30 years, with a mean of 25.79 years (SD = 3.3). The median age was 26 years, indicating that half of the 895 participants were 26 or younger. Most participants (61.7%) as seen in the Distribution of Age chart 5.1 lie in the age bracket of (25 -30), This age profile suggests the program primarily engages young adults who may be transitioning into employment or seeking stable livelihoods

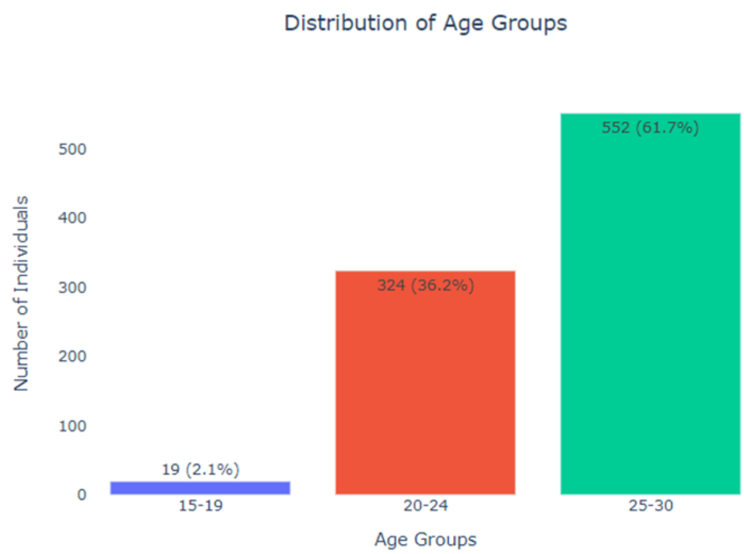

Figure 5.1: Age Group Distribution

5.2.2. Gender Distribution

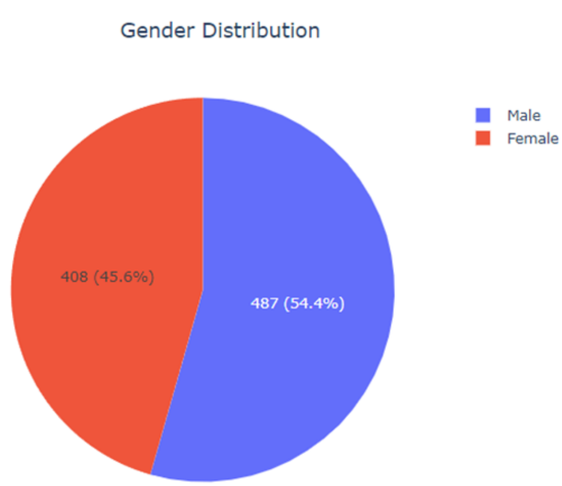

Figure 5.2: Gender Distribution

The gender distribution chart 5.2 shows a slight predominance of males, making up 54.4% of the participants, compared to 45.6% of females. This distribution is near equal balance between genders. The close split indicates the program was accessible to both genders.

5.2.3. Education Level Distribution

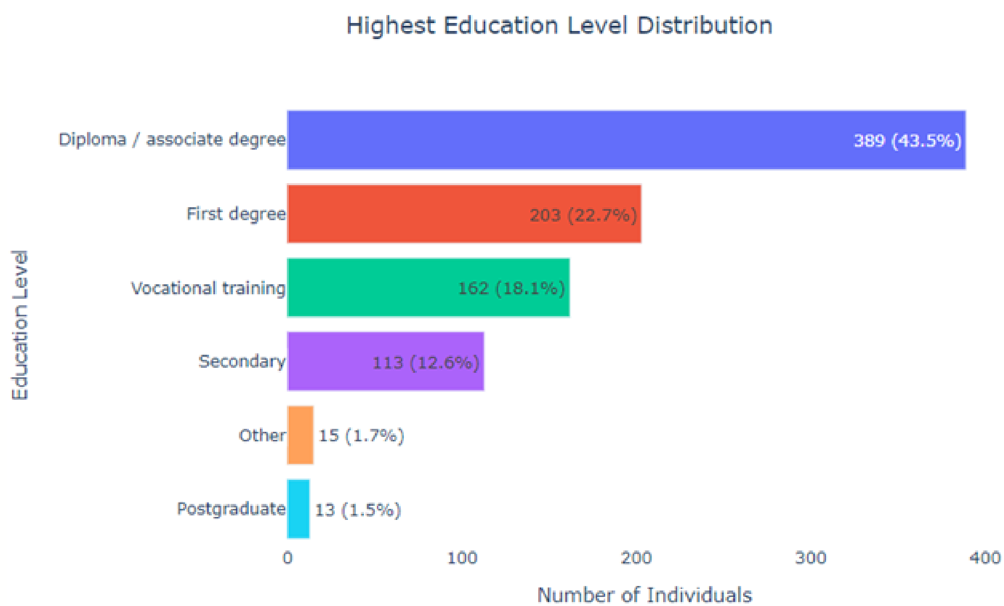

Figure 5.3: Education Level Distribution

The education level statistics offer valuable insights into the participant profile of the economic empowerment programs. Most of the participants hold a diploma or associate degree (43.5%, 389 individuals), followed by the first degree (22.7%, 203 individuals) and vocational training (18.1%, 162 individuals). This dissemination shows that the programs largely attract youth with some post-secondary education, indicating a targeting of those who have experienced higher formal or technical education. The high percentage of trainees with vocational training indicates the inclusivity of the programs of different educational pathways, of specific relevance to addressing the heterogeneous needs of youth with disabilities.

In contrast, those with only secondary education make up a smaller group (12.6%, 113 participants), and this may indicate current barriers to access or participation for those with lower educational levels. Program eligibility, program design, or outreach may be the cause of this difference, and this needs to be examined more closely to promote greater inclusiveness. Concurrently, the postgraduate (1.5%, 13 individuals) and 'Other' (1.7%, 15 individuals) cohorts constitute extremely small proportions, which can suggest that the programs are either not appropriate for or appealing to those with higher qualifications or non-traditional educational backgrounds.

5.2.4. Disability Type Distribution

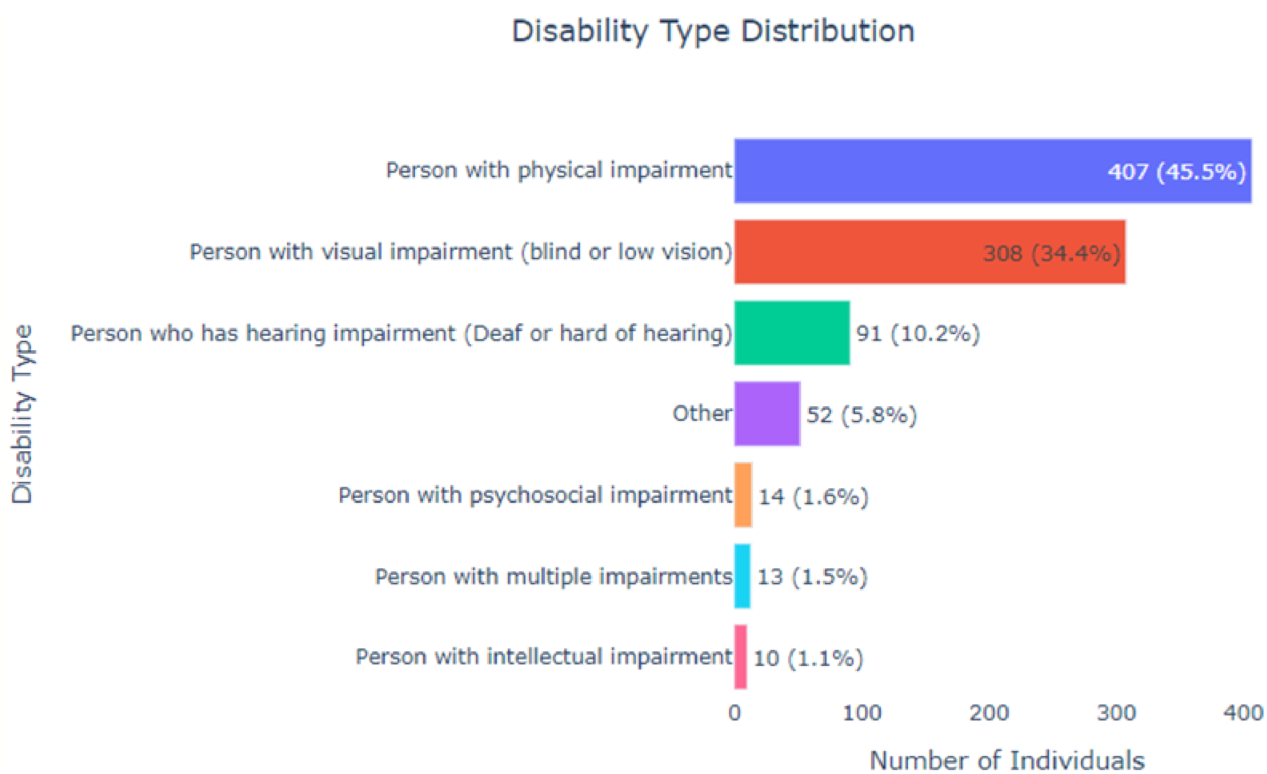

Figure 5.4: Disability Distribution

Most participants have physical impairments (45.5%) or visual impairments (34.4%), making up nearly 80% of the group. Hearing impairments are less common at 10.2%, while other types—like psychosocial (1.6%), multiple (1.5%), and intellectual impairments (1.1%)—are much rarer, each below 2%. This shows that the programs are mainly reaching people with physical and visual impairments. It could mean these disabilities are more common or that the programs suit their needs better. However, the small numbers of participants with psychosocial, multiple, or intellectual impairments suggest these groups might face barriers, like stigma or lack of support, keeping them from joining.

5.3. Drivers of successful employment in economic empowerment programs for youths with disabilities

In this section, we present the key factors that significantly influence whether youth with disabilities secure employment after participating in economic empowerment programs. We employed a multi-faceted approach looking at correlation analysis, logistic regression, and machine learning feature importance. The findings below detail the results from these methods and their implications for program design.

5.3.1. Correlation Analysis

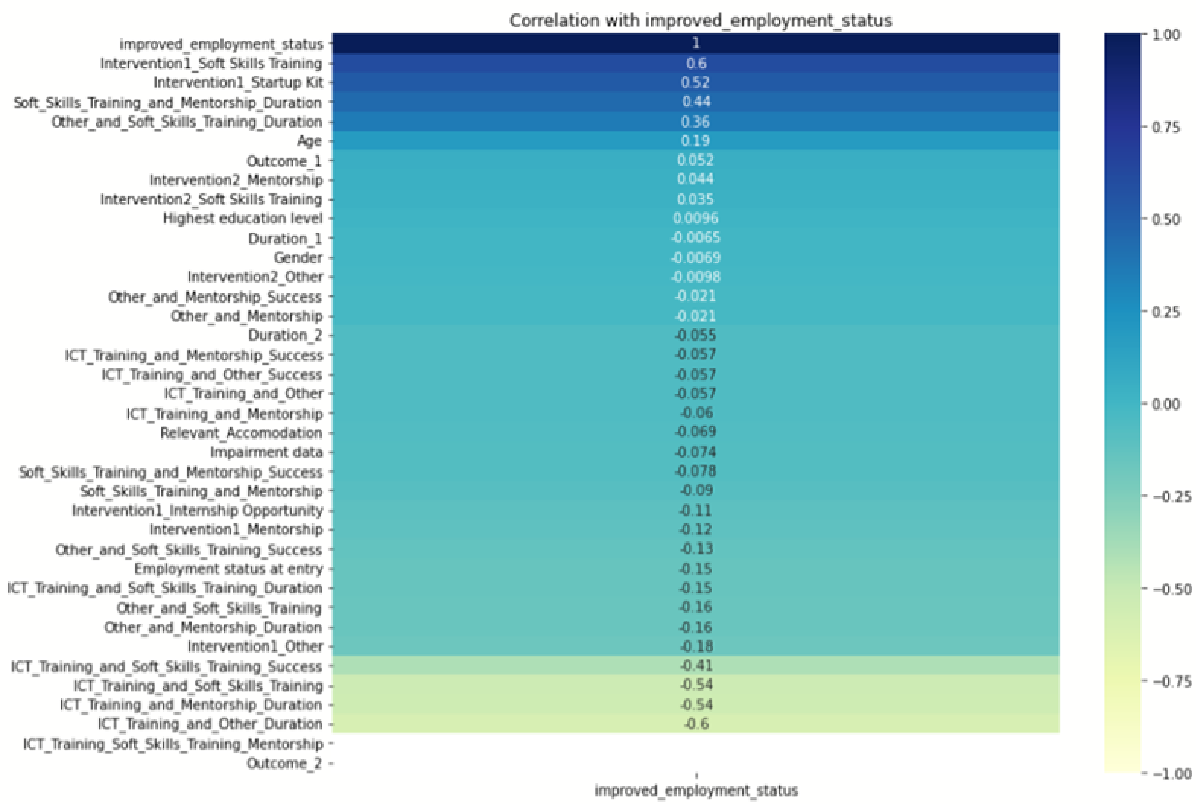

Figure 5.5: Correlation Heatmap

We first explored correlations between potential drivers and employment outcomes. Factors included intervention type, intervention duration, intervention order and combinations, and demographics such as age, gender, education and disability type. To identify these relationships, we visualized the correlation as seen in Figure 5.5, a correlation heatmap.

(a) Soft skills training ($r = 0.45$, $p<0.001$): The correlation coefficient of 0.45 indicates a moderate to strong positive relationship between attending soft skills training e.g. (communication, teamwork, problem-solving) and the likelihood of securing employment. The p-value of less than 0.001 confirms that the relationship is indeed statistically significant, suggesting soft skills training is a critical component of employment success.

(b) Startup Kit provision ($r = 0.517$, $p = 2.62e-62$): With a correlation coefficient of 0.517, the provision of start up kits to the participants demonstrates a stronger association with employment outcomes. The small p-value of ($p = 2.62e-62$) further affirms it, suggesting that access to start up resources enhances the ability of the youth with disabilities to gain employment.

(c) Soft Skills Training and Mentorship duration ($r = 0.441$, $p = 6.12e-44$) :The duration of the combination of soft skills training and mentorship shows a strong moderate correlation with employment outcomes of 0.441. Coupled with the p-value of 6.12e-44, this gives an indication that longer periods for these interventions substantially increase their effectiveness.

Certain intervention combinations, such as ICT (information and communication technology) training paired with other interventions, exhibited weaker positive correlations or, in some cases, slightly negative correlations with employment outcomes. This suggests that while ICT training may have value, its effectiveness could depend on how it is implemented or whether it aligns with local job market demands. Variables like age, gender, and education level showed weaker correlations with employment outcomes compared to intervention-related factors. This implies that while demographics may influence success to some extent, the type and quality of program interventions are more decisive drivers.

5.3.2. Logistic Regression Analysis

To build on the correlation analysis and quantify the effect of each feature on the probability of improving employment status, we conducted a logistic regression analysis. A logistic regression model was fitted to the data, with "improved_employment_status" as the dependent variable and all other factors as independent variables. The model yields coefficient for each feature, indicating the direction and strength of their relationship with the outcome variable, and the odds ratio, which quantifies how much the odds of improved employment change with a one-unit increase in the feature.

Feature	Coefficient	Odds Ratio
Intervention1 Soft Skills Training	2.063	7.869
Intervention1 Startup Kit	1.889	6.611
Age	0.389	1.475
Soft Skills Training and Mentorship Duration	0.262	1.299

Table 5.2: Feature Coefficients and Odds Ratios

(a) Intervention 1 - Soft Skills training (Coefficient: 2.063, Odds Ratio: 7.869): According to the Odds ratio, participants who received soft skills training as their first intervention were nearly 8 times more likely to improve their employment status, holding other factors constant.

(b) Intervention1 Startup Kit (Coefficient: 1.889, Odds Ratio: 6.611): Providing a startup kit as the first intervention increased the odds of improved employment by over 6.5 times.

(c) Age (Coefficient: 0.389, Odds Ratio: 1.475): Each additional year of age increased the odds of improved employment by approximately 1.5 times. Older participants may leverage maturity or experience to enhance their employment outcomes.

(d) Soft Skills Training and Mentorship Duration (Coefficient: 0.262, Odds Ratio: 1.299): Longer durations of combined soft skills training and mentorship modestly increased the odds of improved employment outcome, suggesting sustained engagement enhances effectiveness.

5.3.3. Feature Importance from Machine Learning

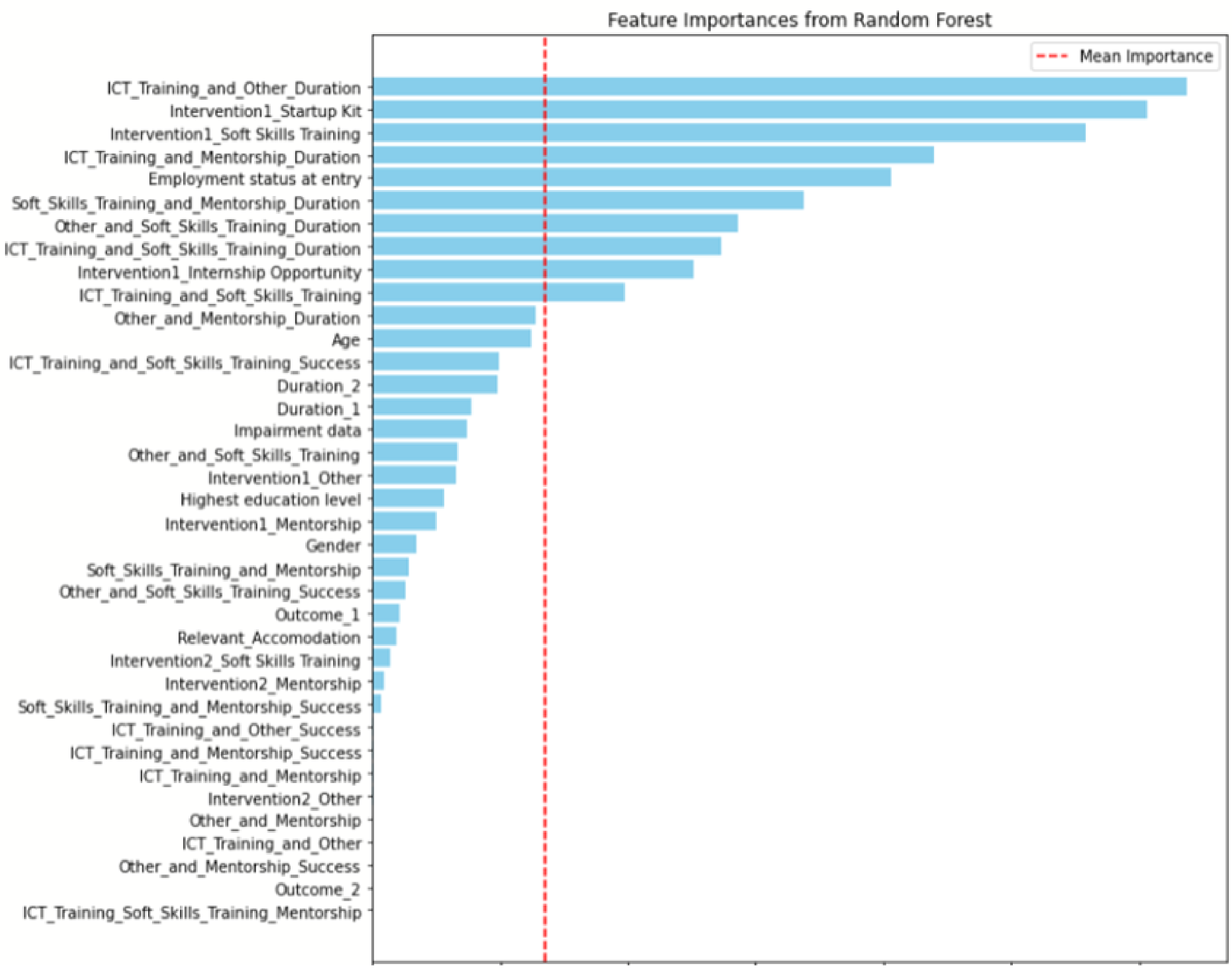

Figure 5.6: Feature Importance from Machine Learning

To complement the correlation and logistic regression analyses, we utilized a machine learning approach to further uncover the drivers of employment success for youth with disabilities. A Random Forest classifier was employed to identify the most influential features in predicting the binary outcome of "improved_employment_status". This method provides a non-linear perspective, capturing complex interaction between variables that may have been missed by statistical models. The selected features are ('Intervention1 Internship Opportunity', 'Intervention1 Soft Skills Training', 'Intervention1 Startup Kit provisioning', 'ICT Training and Soft Skills Training', 'ICT Training and Other Duration', 'ICT Training and Soft Skills Training Duration', 'ICT Training and Mentorship Duration', 'Other and Soft Skills Training Duration', 'Soft Skills Training and Mentorship Duration', 'Employment status at entry')

The analysis revealed several key insights consistent with earlier findings. For example, Early Intervention features like Intervention1 Internship Opportunity, Intervention1 Soft Skills Training, and Intervention1 Startup Kit emphasize the critical role of early interventions. This aligns with the logistic regression results (e.g., odds ratios of 7.869 for soft skills training and 6.611 for startup kits) and correlation analysis ($r = 0.45$ for soft skills training, $r = 0.517$ for startup kits), reinforcing their importance in driving employment success. Combination and Duration features like "Soft Skills Training and Mentorship Duration (correlation $r = 0.441$, odds ration 1.299) and ICT training and Soft Skills Training Duration suggest that longer, combined interventions enhance the effectiveness, a pattern also observed in statistical analysis.

5.3.4. Summary on Key Drivers

The correlation analysis, logistic regression, and machine learning feature importance collectively identify soft skills training, startup kit provision, and the duration of mentorship as key drivers of employment success. These findings suggest that resource-based and sustained interventions are critical for youth with disabilities. The logistic regression analysis quantifies the substantial impact of early interventions, while the machine learning approach highlights the importance of intervention combinations and participant characteristics. Together, these insights provide a data-driven foundation for optimizing economic empowerment programs

5.4. Machine Learning model to predict employability

Using data from 895 participants in economic empowerment programs in Uganda, we first constructed baseline models and then Ensemble model to predict the target binary outcome "Improved Employment Status" (Yes/No) for employability prediction. This subsection evaluates models' performances, identifies key predictors, and demonstrates its practical utility, supported by visualizations to clarify findings

5.4.1. Baseline Model Performance

Our initial evaluation examined the predictive capabilities of three baseline classification models (Decision Tree, K-Nearest Neighbors (KNN), and Logistic Regression utilizing metrics such as accuracy, precision, recall, and F1-scores. From the selected baseline models, the K-Nearest Neighbors (KNN) performed best, achieving the highest accuracy of 91.06% with F1 mean of 85.19%. Decision Tree model followed, attaining an accuracy of 90.50% and an F1 score of 84.96%, which suggests dependable generalization. In contrast, Logistic Regression recorded a low accuracy of 80.45% and an F-Score of 74.07%. Considering these findings, we explored ensemble models to further enhance prediction robustness and reliability as they are better at capturing complex relationships.

5.4.2. Ensemble Model Performance

The ensemble models showed great performances, with Gradient Boosting achieving an accuracy of 96.21%, F1-score 96.15%, followed by both XGBoost and Random Forest achieving similar accuracy of 94.41% and F1-Score 98.08%). The Stacking Ensemble model combines Random Forest, XGBoost, and Gradient Boosting as base learners, with a Logistic Regression meta-learner integrating their predictions for improved accuracy.

The Stacking Ensemble excelled on the test set with an Accuracy of 97.21%, Precision of 92.73%, Recall of 98.08%, F1-Score 95.33%, and AUC-ROC of 99.58%, reinforcing the effectiveness of combining multiple models to enhance predictive performance.

Table below compares its performance against baselines like Logistic Regression and Random Forest, proving its superiority.

Table 5.3: Performance Comparison of Different Models

Models	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Baseline Models					
K-Nearest Neighbors	91.06 %	82.14 %	88.46 %	85.19 %	97.94 %
Decision Tree	90.50 %	78.69 %	92.31 %	84.96 %	93.78 %
Logistic Regression	80.45 %	60.24 %	96.15 %	74.07 %	94.97 %
Ensemble Models					
Random Forest	94.41 %	85.00 %	98.08 %	91.07 %	99.54 %
XGBoost	94.41 %	85.00 %	98.08 %	91.07 %	99.72 %
Gradient Boosting	96.09 %	90.91 %	96.15 %	93.46 %	99.61 %
Stacking Ensemble	97.21 %	92.73 %	98.08 %	95.33 %	99.58 %

The Stacking Ensemble showed exceptional performance in predicting whether employment status of youth with disabilities has improved or not as visualized on the confusion matrix in 5.7 below. Out of 179 cases, the Stacking Ensemble recorded only 5 misclassifications, this included 1 false positive (predicting an improvement when none occurred) and 4 false negatives (failing to predict an employment that did occur). Correctly identifying 123 of 127 Class 0 (Non improvements) and 51 out of 52 of Class 1 (improvements), shows a balanced performance with uneven class distribution.

The confusion matrix confirms the key performance metrics, e.g. Accuracy which is calculated as (True Negatives + True Positives) / Total = (123 + 51) / 179 ≈ 97.2%, reflecting the model's high reliability. The Precision of class 1 (Improved Employment) is calculated as True Positives / (True Positives + False Positives) = 51 / (51 + 4) ≈ 92.7%. This indicates that when the model predicts an improvement, it is correct 92.7% of the time, and the Recall of Class 1 calculated as True Positives / (True Positives + False

Negatives) = 51 / (51 + 1) ≈ 98.1%. This high recall presents the model's ability to identify nearly all instances of actual improvement.

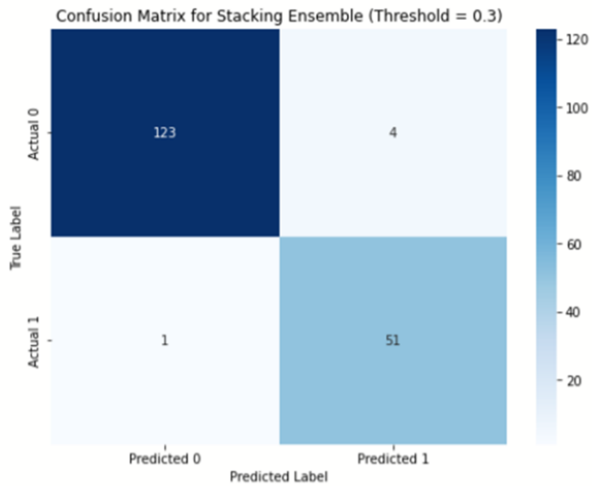

Figure 5.7: Confusion Matrix - Stacking Ensemble

The Receiver Operating Characteristics (ROC) curve was used to visualise the true positive rate (TPR) against the false positive rate (FPR) across various classification thresholds. The Area Under the Curve (AUC) was utilized to evaluate the overall effectiveness of our binary classification model, Figure 5.8 below plots the ROC curve, confirming excellent classification with an AUC of 0.9958.

The AUC-ROC analysis validates that all four ensemble models effectively distinguish between classes displaying strong and dependable classification performance.

5.5. Summary of Key Findings

The demographic data of the participants revealed a predominance of young adults aged 25-30 years with diploma-level education and physical impairments. Statistical and machine learning analyses identified soft skills training and start-up kit provision as the most significant drivers employment success, while training in ICT had a surprisingly weaker impact. The stacking ensemble model demonstrated superior predictive capabilities with an accuracy of 97.21% and a recall of 98.08% making it a valuable tool

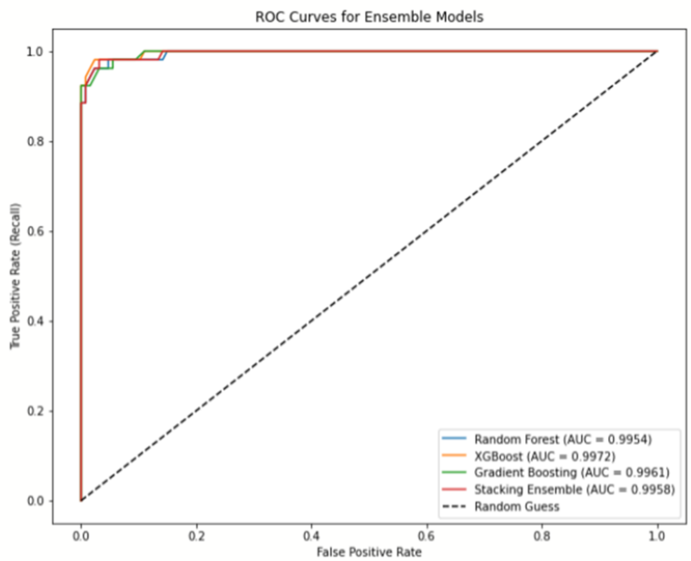

Figure 5.8: ROC Curves - Stacking Ensemble

for identifying youth who are most likely to to benefit from economic empowerment programs. These finding lay the foundation for a discussion on implications, limitations and potential future research.

6. DISCUSSION

6.1. Introduction

The findings from the study provides valuable key insights into the factors influencing employment outcomes for youth with disabilities in Uganda and demonstrates the potential of leveraging machine learning to improve the effectiveness of economic empowerment initiatives. By analyzing program data for 895 participants in programs for empowering youth by Ministry of Gender, Labour and Social Development, we did not only identify the key drivers of employment success but also constructed a predictive model with high accuracy to support data-driven decision making. This discussion interprets the results aligned to the study's objectives, explores their practicality and points out the limitations and recommendations for future research.

6.2. Interpretation of Key Findings

The study's findings uncover key insights in to the factors driving employment success for youth with disabilities and the efficacy of machine learning in predicting these outcomes.

6.2.1. Factors Influencing Employment Outcomes

The study identified key factors that significantly inform employment success for youth with disabilities. The correlation analysis, logistics regression, and feature importance from the Random Forest classifier collectively identified soft skills training and start-up kit provision as critical factors which align with existing literature on barriers on barriers for marginalized groups (Lindsay et al., 2021). For instance, program participants who got soft skills training as their first intervention were almost eight times more likely to get a positive employment outcome (odds ration =7.869, $p<0.001$). In the same way, those who received business startup kits increased their odds of improved employment outcome by more than 6 times (odds ration = 6.661, $p<0.001$). These results side with the reviewed literatures, which emphasize the importance of vocational training and resource provision in overcoming employment barriers for marginalized groups (Batchuluun et al., 2017). Soft skills like communication and teamwork are vital for youth with disabilities as they often suffer from challenges in workplace integration due to stigma and accessibility issues.

Another significant driver was the impact of intervention duration, especially for combinations of soft skills training and mentorship. Longer exposure to the interventions was associated with better outcomes. This suggests that the longer duration is crucial for building confidence and the skills needed for sustainable employment.

While our study confirmed the impact of soft skills training and startup kit support as important predictors, there was a weaker correlation between ICT training and employment success. This was unexpected given the rapidly advancing digital age. The correlation showed a weak positive correlation ($r=0.12$, $p=0.045$) supported by logistic regression failing to identify ICT training as a significant predictor. This result may be because of mismatch of ICT Skills taught and actual demand of the local job market in Uganda there by participants not finding practical application of the skills. It could also be that the lack of accessible technology for youth with disabilities hinders the practical application of these skills.

These findings point out the need for youth empowerment initiatives to align the training with the local employment opportunities and ensure participants have the right tools and accommodations to apply the learnt skills effectively. It also highlights the importance of understanding the economic and social context in which these initiatives are implemented.

6.2.2. Predictive Model Performance

The main objective of our study was to develop a machine learning algorithm to predict employment outcomes for youth with disabilities to enhance the effectiveness of economic empowerment programs. The Stacking Ensemble model that integrated Random Forest, XGBoost, and Gradient Boosting classifiers achieved a high performance with an accuracy of 97.21%, recall of 98.08%, and an F1-Score 95.33%. These metrics indicate the model's ability to reliably predict if a participant's employment status will improve given specific interventions. The nearly perfect recall confirms that the model can identify most instances where employment status improves, making it a balanced tool.

6.2.3. Comparison of the Proposed Model with Existing Employment Prediction Models

The performance of the proposed Stacking Ensemble model was compared with related machine learning studies on employment and employability prediction reviewed in the Literature Review section. Previous studies have shown that machine learning models can be useful in predicting employment related outcomes although most of them were conducted in different contexts and with different populations. For example, Sobnath et al. (2020) reported 0.96 accuracy using Logistic Regression on a large dataset of disabled students, while Griffiths et al. (2023) reported an accuracy of about 0.93 using a Decision Tree Classifier for autistic youth. Broda et al. (2021) reported 0.89 accuracy with the application of Random Forest classifier for people with intellectual and developmental disabilities, while Sun and He (2023) reported strong Support Vector Machine performance with 0.90 precision, 0.88 recall and 0.93 accuracy. In comparison, this study's Stacking Ensemble achieved 97.21% accuracy, 92.73% precision, 98.08% recall, 95.33% F1-score and 99.58% AUC-ROC. These results show that the proposed model performed strongly within the study dataset. However, this comparison should be interpreted with caution becauses the studies were conducted in different contexts, datasets, populations, and sample sizes.

6.3. Practical Implications and Recommended Model for Use

Organisations that design and implement economic empowerment programs for youth with disabilities could find this model of a practical value. Based on the model comparison, the Stacking Ensemble would be the most suitable model to recommend for predicting employment outcomes. This is because it performed best across the key evaluation metrics, achieving 97.21% accuracy, 92.73% precision, 98.08% recall, and 95.33% F1-score. The high recall is particularly important because it means the model was able to correctly identify most of the participants whose employment status actually improved. This model could help program teams make more informed decisions. For example, it could support the identification of participants who may need additional support, or help program officers understand which intervention combinations are more likely to be associated with improved employment outcomes. The findings also suggest that interventions such as soft skills training, startup kits, mentorship, and sustained support should receive more attention in future program design.

However, the model should not be used as an automated decision-making tool. It should only be used to support judgement by program managers and officers. This is key because the study focuses on youth with disabilities, a marginalized group. The model should therefore be used to identify where more support may be needed, not to deny anyone access to services.

Before an organisation fully adopts the model, it should first test it using its own historical program data. It should also be validated by applying it to new participants and comparing the predicted outcomes with actual follow-up outcomes. This would help confirm whether the model performs well outside the research dataset.

6.4. Limitations

Despite the strengths of our study, there are several limitations that we acknowledge. First the dataset was relatively small with only 895 observations which may limit the generalizability of the findings and the model's predictive performance to toeher regions or economic empowerment programs. Secondly, the study relied on historical program data that may contain biases or inaccuracies. Given the domain knowledge, the dataset also may not have fully captured relevant factors influencing employment outcomes, such as family support or economic conditions. Also, the study's focus on program participants exclude youth with disabilities who did not enroll, this introduces selection bias.

Another limitation is that the model was evaluated using the available program dataset and has not been validated externally in a live organisational setting. Although the internal performance was strong, organisations may have different intervention style, participants profiles, data quality issues and follow-up processes. For this reason, the model should be validated with external datasets before full deployment.

In conclusion, while the machine learning algorithms have great prediction capabilities, they don't prove that the interventions are actual reasons for improved employment outcomes. Further studies need to be undertaken to establish relationships.

6.5. Recommendations

Building on our study findings, the predictive model could be tested in different geographical and economic contexts to determine its generalizability. This adaptation to other low-income countries or regions with varying employment settings would help ascertain its broader applicability.

The model could be further tuned to provide personalized recommendations integrated into an information management system such as dashboards, enabling real-time monitoring of participants' progression.

The weaker impact of other interventions like ICT training deserves further investigation. Qualitative studies with participants and employers could provide better analysis into why these interventions were less effective and how it could be streamlined.

Organisations interested in using the model should adopt it gradually. The first step would be to test the model using historical data from other economic empowerment programs or regions. This would help ascertain if the model performs beyond the dataset used in the study. The organisation can then validate the model by applying it to new participants and later comparing the predicted results with the actual follow-up results.

Finally, future studies building on this could incorporate additional socio-economic variables like family income, social support, access to transportation to refine the predictive model.

6.6. Machine Learning Contribution of the Study

The machine learning contribution of this study is that it demonstrates how supervised classification models can be applied to predict improved employment status among youth with disabilities in economic empowerment programs. Rather than relying on one model, the study compared both simple baseline models and more advanced ensemble models to identify the most suitable approach for the prediction task.

The technical contribution is in the full modelling process used, from preparing the data, engineering intervention-related features, selecting important predictors, tuning model parameters, validating performance using cross-validation, and comparing models using several evaluation metrics. The best-performing model was the Stacking Ensemble, which showed that combining different algorithms can improve prediction where employment outcomes are influenced by several interacting factors.

6.7. Conclusion

In summary, our investigation has revealed the potential of using machine learning algorithms to predict the employment outcomes for youth with disabilities participating in economic empowerment programs. We identified key drivers of employment such as soft skills training and study kit provision. These findings point out the importance of tailored interventions to break employment barriers. The model's high accuracy offers a promising tool for program effectiveness, the study also highlights areas of improvement like aligning ICT training with local job markets. By addressing these challenges and building on our study, employment opportunities can further be enhanced for marginalized group contributing to a more inclusive labour market in Uganda.

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